

Received: 04 Feb. 2026; Revised: 19 May 2026; Accepted: 27 Aug. 2026
<https://doi.org/10.22306/al.v13i3.813>

AI agents for decision support in logistics management: a literature review

Diana Sánchez-Partida

Faculty Industrial Systems (FIS), UPAEP - SECIHTI Puebla, 21 south 1103 Barrio Santiago, ZC 72410, Puebla, Mexico, diana.sanchez@upaep.mx (corresponding author)

Emmy Getsel Sánchez-Cordova

Department of Physics, Mathematics and Engineering, University of Sonora, Lázaro Cárdenas No. 100, ZC 85880, Navojoa, Sonora, Mexico, emmy.sanchez@unison.mx

Manuel Romero-Julio

Faculty of Engineering and Business, UDLA University, Manuel Montt 948, Providencia, Chile, mromeroj@udla.cl

Keywords: intelligent agents, multi-agent systems, logistics management, supply chain, resilience.

Abstract: The increasing complexity, volatility, and sustainability pressures affecting global supply chains have accelerated the adoption of Artificial Intelligence (AI) technologies in logistics management. Among these AI approaches, Intelligent Agents (IAs) and Multi-agent Systems (MAS) have emerged as essential tools for supporting decentralized, adaptive, event-driven, and real-time decision-making processes in dynamic logistics environments. Unlike traditional centralized planning systems, agent-based approaches enable autonomous entities such as suppliers, warehouses, transportation units, and distribution centers to coordinate actions, exchange information, and manage variability. This paper presents a structured literature review of peer-reviewed studies indexed in Scopus and Web of Science on the use of AI agents to support decision-making in logistics management and supply chain operations. Particular attention is given to the strategic importance of intelligent agents in strengthening resilience, operational efficiency, and sustainability in increasingly uncertain logistics systems. The findings indicate that intelligent agents improve decision quality, responsiveness, coordination, and resource utilization across distributed logistics networks. Furthermore, Multi-Agent Systems enhance interoperability and collaboration among logistics actors, enabling more agile and resilient supply chains. However, challenges related to data quality, cybersecurity, governance, scalability, and human–AI collaboration continue to limit large-scale implementation in industrial environments.

1 Introduction

Logistics systems are exposed to increasing uncertainty derived from demand variability, supply disruptions, geopolitical tensions, climate-related events, and sustainability requirements. Traditional centralized planning tools often struggle to respond in real time to events across distributed networks of suppliers, carriers, warehouses, and customers [1].

Within the broad field of Artificial Intelligence (AI), Intelligent Agents (IAs) and Multi-Agent Systems (MAS) have emerged as promising paradigms for modeling logistics operations in dynamic and distributed environments. Agent-based systems enable autonomous entities to interact, exchange information, and coordinate decisions in response to changing operational conditions. In logistics and supply chain contexts, agents may represent suppliers, transportation units, warehouses, planners, or organizations capable of coordinating actions to achieve local and global objectives. Through these interactions, Multi-Agent Systems support flexibility and responsiveness in supply chain operations under uncertainty, making them relevant approaches for modern logistics management [2].

Foundational work highlights that transportation and supply chain planning problems are natural candidates for distributed decision architectures [3]. More recent reviews also show a broad spectrum of MAS applications for planning, coordination, and control across supply chains [4].

In parallel, advances in data infrastructure, IoT, cloud computing, and reinforcement learning have enabled more sophisticated agentic AI, in which software agents continuously sense, reason, and act on large volumes of operational data. Empirical studies and conceptual analyses suggest that intelligent agents will increasingly orchestrate cross-functional supply chain decisions, autonomously executing operational choices within predefined constraints [5].

This paper addresses the following research question:

How do AI-based agents support decision-making in logistics management, and what benefits, limitations, and research gaps have been identified in the Scopus and Web of Science literature and in other aspects?

2 Methodology framework

2.1 Literature search strategy

This study employed a structured literature review approach based on peer-reviewed journal articles and conference proceedings retrieved from the Scopus and Web of Science (WoS) databases. The search focused on studies that address the application of AI agents in logistics decision-making contexts. The initial database search retrieved approximately 64,600 records.

The search strategy used combinations of keywords associated with intelligent agents, logistics, and decision-making, which were applied to titles, abstracts, and author keywords:

(“Intelligent agent” OR “software agent” OR “multi-agent system” OR “agent-based”)
AND
(“logistics” OR “supply chain” OR “transportation” OR “warehouse” OR “inventory”)
AND
(“decision making” OR “decision support” OR “planning” OR “scheduling”)

Titles and abstracts were screened, excluding records that did not address AI agents or logistics decision-making as central topics. Of the remaining 125 full-text articles assessed for eligibility, 65 were excluded due to insufficient agent-based information, purely descriptive scope, or lack of decision-making focus. Therefore, 60 records identified through snowballing and manual searches of key journals were incorporated, resulting in a final corpus of core papers, which were subjected to thematic synthesis and coding.

The time window was open (from the earliest available to 2025) to capture both foundational MAS work and recent applications of agentic AI in operations.

Additional articles were identified by snowballing from the reference lists of key papers and scanning recent volumes of logistics and operations journals.

2.2 Study selection criteria

The selected studies met the following conditions:

- addressed logistics or supply chain operations (transportation, warehousing, inventory, production scheduling, risk management, humanitarian logistics);
- used AI agents, MAS, or agent-based models as a central modeling or implementation paradigm;
- focused on decision making (planning, scheduling, routing, allocation, risk mitigation) rather than purely descriptive simulation.
- Works limited to conceptual discussions of Industry 4.0 or Logistics 4.0 without explicit agent models, or purely predictive models without autonomous decision making, were excluded or used only as contextual background.

2.3 Analysis and synthesis

The selected articles, 60 core papers, were coded along the following dimensions:

- Logistics function and decision level (strategic, tactical, operational, and real-time execution).
- Agent architecture type (single-agent, MAS, hybrid with centralized coordinator).
- AI techniques employed (rule-based agents, reinforcement learning, metaheuristics, fuzzy-rough sets, Bayesian networks).
- Application context (urban logistics, container terminals, Ro-Ro terminals, warehouses, production systems, humanitarian supply chains).
- Reported benefits and limitations associated with AI-agent implementation in logistics decision-making.

A thematic synthesis was then conducted to identify recurring patterns in how AI agents support logistics decision-making, the benefits obtained, and limitations reported (Table 1):

Table 1 Articles 60 core papers

Ref.	Reference	Logistics Function & Level	Agent Architecture type	AI Technique	Implemented?	Key Benefits	Key Limitations
[1]	Baryannis et al. (2019)	Risk mgmt tactical	MAS	AI + DSS hybrid	No	Risk insights	Low empirical validation
[2]	Kaihara (2003)	SC modeling tactical	MAS	Optimization agents	No	Dynamic modeling	High abstraction
[3]	Wadhwa & Bibhushan (2006)	SC modeling tactical	MAS	Simulation	No	Clear models	No deployment
[4]	Dominguez & Cannella (2020)	SC control tactical	MAS	Rule-based	No	Clear MAS structure	No field validation

AI agents for decision support in logistics management: a literature review

Diana Sánchez-Partida, Emmy Getsel Sánchez-Cordova, Manuel Romero-Julio

[5]	Xu et al. (2021)	SC automation strategic	–	MAS	Automation agents	No	Automation roadmap	Theoretical
[6]	Singh (2003)	SC coordination strategic	–	Single agent	Knowledge-based agents	No	Foundational framework for agent roles in information systems	Conceptual only; no logistics-specific validation
[7]	Herzog & Timm (2021)	Smart logistics operational	–	MAS	Learning agents	No	Knowledge adaptation	No pilot application
[8]	Grundspenkis (2008)	Logistics automation operational	–	MAS	Knowledge-based	No	Conceptual strength	No empirical data
[9]	Govindu & Chinnam (2007)	SC coordination tactical	–	MAS	Rule-based	No	Collaboration gains	Not tested
[10]	Akanle & Zhang (2008)	SC design strategic	–	MAS	Optimization + heuristics	No	Flexible SC design	Complex calibration
[11]	Julka et al. (2002)	SC decision support – tactical	–	MAS	Agent-based modeling framework	No	Integrated multi-enterprise decisions	Tested only in refinery DSS prototypes
[12]	Shukla & Kiridena (2016)	SC configuration tactical	–	MAS	Fuzzy-rough agents	No	Multi-criteria modeling	Parameter tuning
[13]	Böhllein et al. (2011)	Transport planning – tactical	–	MAS	Heuristic coordination	Yes	Efficiency gains	Data integration effort
[14]	Schleiffer (2002)	Traffic control operational	–	MAS	Reactive agents	Yes	Flow improvement	Older data
[15]	Bazzan et al. (2005)	Traffic routing operational	–	MAS	Reinforcement + rules	Yes	Adaptive routing	Scalability issues
[16]	Kahalimoghdam et al. (2025)	Last-mile operational	–	MAS	RL agents	No	Routing improvements	Not deployed
[17]	Helo & Rouzafzoon (2023)	Timber logistics operational	–	MAS	Simulation + optimization	Yes	Improved routing	Context specific
[18]	Salas-Rodríguez & Rivas-Tovar (2022)	Transport infrastructure tactical	–	MAS	Simulation	No	Scenario modeling	No RL
[19]	Krnjaic et al. (2024)	Warehouse order picking operational	–	MAS	Hierarchical multi-agent RL	No	Higher pick rates than heuristics	Simulation-based evaluation
[20]	Um et al. (2010)	SC coordination tactical	–	MAS	Rule-based	No	Coordination modeling	No validation
[21]	Li & Epureanu (2020)	Fleet allocation operational	–	MAS	Simulation heuristics	No	Allocation gains	Model complexity
[22]	Terrada et al. (2020)	SC management tactical	–	MAS	Hybrid	No	Structured approach	No field test
[23]	Chen et al. (2013)	SC risk operational	–	MAS	ABM	No	Disruption modeling	No live pilots
[24]	Bugert & Lasch (2023)	Risk propagation tactical	–	MAS	Bayesian + ABM	No	Deep risk modeling	High computational cost
[25]	Nadi et al. (2023)	Slot mgmt execution	–	MAS	Data-driven agents	Yes	Delay reduction	Terminal-specific
[26]	Rodríguez-Espíndola et al. (2023)	HL optimization – strategic	–	MAS	ABM	No	HL insights	No implementation
[27]	Liao et al. (2023)	Humanitarian structures operational	–	MAS	Simulation	No	Structure insights	No implementation
[28]	Rezki & Mansouri (2024)	Supplier risk tactical	–	Single agent	ML/DL	No	Better prediction	High data demand
[29]	Davidsson et al. (2005)	Transport chains operational	–	MAS	Simulation agents	No	Chain understanding	No RL integration
[30]	Espejo-Díaz (2020)	Humanitarian IRP – tactical	–	MAS	Simulation + heuristics	No	Robust scenarios	No deployment
[31]	Hernández et al. (2009)	Collaboration tactical	–	MAS	Negotiation agents	No	Better coordination	High model complexity
[32]	Li & Chan (2013)	Dynamic SC tactical	–	MAS	ABM	No	Adaptive behaviors	No industry case
[33]	Xu et al. (2024)	Autonomous SC – strategic	–	MAS	Agent architecture + toolkit	No	Implementation methodology	Single case study
[34]	Jaimez-González & Luna-Ramírez (2021)	SCM architecture – strategic	–	MAS	Hybrid	No	Clear architecture	Not implemented
[35]	Lujak et al. (2021)	Traffic coordination operational	–	MAS	Control agents	Yes	Higher flow efficiency	Requires IoT

AI agents for decision support in logistics management: a literature review

Diana Sánchez-Partida, Emmy Getsel Sánchez-Cordova, Manuel Romero-Julio

[36]	Mes et al. (2013)	Real-time routing – execution	MAS	Learning heuristics	+	Yes	Fast re-routing	Data dependency
[37]	Gerrits et al. (2024)	Self-organizing transport strategic	MAS	Review typology	+	No	Autonomy–cooperativity framework	Conceptual
[38]	Moreno et al. (2025)	Pickup–delivery – execution	MAS	Simulation + ML		No	Routing optimization	Simulation only
[39]	Nitsche et al. (2023)	Autonomous logistics – tactical	MAS	Hybrid		No	MAS roadmap	No validation
[40]	Pal (2015)	Transport corridors – tactical	MAS	Simulation		No	Corridor insights	Simplified behaviors
[41]	Staruch (2023)	Production planning operational	MAS	Smart agents		No	Better planning	Prototype only
[42]	Swaminathan et al. (1998)	SC dynamics – strategic	MAS	Negotiation agents		No	Foundational model	No implementation
[43]	Ulmer (2020)	Same-day routing – execution	Single agent	RL + heuristics		No	Adaptive decisions	Needs live data
[44]	Labelle & Frayret (2023)	Reverse logistics – tactical	MAS	ABM		No	Forecasts voluntary return rates	Region-specific data
[45]	Parmaksizoglou et al. (2025)	Marine terminals – operational	MAS	Multi-agent optimization heuristics	+	No	Coordinated berth and truck scheduling	Computational tests only
[46]	Henesey et al. (2009a)	Terminal AGV systems – operational	MAS	Agent-based simulation		No	Cost-efficient AGV configurations	Simulation only
[47]	Reddy et al. (2017)	Food procurement & cross-docks – operational	MAS	Negotiation agents + PSO		No	Less food waste; better routing	Case-specific
[48]	Macal & North (2010)	SC modeling – strategic	Single agent	ABM methodology		No	Strong methodology	Generic focus
[49]	Henesey et al. (2009b)	Container terminal ops – operational	MAS	Agent-based simulation		No	Shorter ship turnaround	Terminal-specific
[50]	Bastarionto et al. (2023)	Urban transport – tactical	MAS	Bibliometric review of ABM		No	Map of research clusters	Calibration/validation gaps
[51]	Espejo-Díaz & Guerrero (2021)	Post-disaster relief – tactical	MAS	ABM optimization	+	No	Better service levels	Single case (Mocoa)
[52]	Fan et al. (2021)	Cold chain design – strategic	MAS	Agent-oriented simulation		No	Cost–emission–quality trade-offs	Single product case
[53]	Feng et al. (2022)	Ride-sourcing & transit – execution	Single agent	RL + integer programming		No	Better matching efficiency	Simulation with city data
[54]	Fikar et al. (2018)	Disaster relief distribution operational	MAS	ABS optimization	+	No	Improved relief planning	Scenario-based
[55]	Kaddoussi et al. (2013)	Crisis scheduling SC operational	MAS	Distributed scheduling agents		No	Coordinated delivery	Simulation only
[56]	Mes & Douma (2016)	Barge–terminal appointments operational	MAS	Multi-agent planning		No	Higher terminal utilization	Simulation with port data
[57]	Hernández et al. (2014)	SC collaboration – tactical	MAS	Negotiation agents		No	Service level and profit gains	One automotive SC
[58]	Chan et al. (2012)	Air cargo operational	MAS	Agents simulated annealing	+	No	Faster load planning	Prototype system
[59]	Li & Ni (2022)	Rail timetabling – operational	MAS	Multi-agent deep RL		No	Flexible timetabling	Computational tests only
[60]	Zhou et al. (2019)	Ride-hailing dispatch execution	MAS	Multi-agent RL		Yes	Decentralized dispatching	Platform-specific data

Note: MAS = Multi-Agent System

3 Theoretical background

3.1 Intelligent agents and multi-agent systems

In the field of Artificial Intelligence (AI) intelligent agents are autonomous software-based entities capable of perceiving environmental conditions, processing information, and acting to achieve specific objectives [6,61].

Intelligent agents and MAS have been widely applied in manufacturing, logistics, and transportation since the 1990s as a form of distributed artificial intelligence [7,8].

Multi-Agent Systems consist of autonomous agents that interact and cooperate to address complex and distributed problems. These systems are particularly suitable for dynamic environments in which information and decision-making processes are decentralized and require coordinated responses among multiple actors [9].

Several papers explicitly argue that logistics and supply chain management constitute natural domains for MAS due to the presence of numerous autonomous actors and the need for negotiation, contracting, and coordination [3].

3.2 Decision support and agentic AI in logistics

Traditional Decision Support Systems (DSS) in logistics rely on centralized optimization and planning models. While powerful, these architectures may struggle with real-time responsiveness, inter-organizational coordination, and scalability [10].

Agent-based decision support addresses these limitations by distributing decision capabilities among agents representing carriers, warehouses, orders, vehicles, or even market platforms. MAS can be combined with optimization, simulation, and machine learning to build intelligent decision support systems that learn from data while preserving the autonomy of distributed actors [4,11-13].

In logistics, this translates into agent-based transport planning, dynamic routing, distributed inventory decisions, production scheduling, and risk management [2,14].

4 Applications of AI agents in logistics operations

4.1 Transportation and last-mile logistics

Transportation has been one of the earliest and most developed domains for MAS in logistics. Agent-based and multi-agent models represent vehicles, customers, and infrastructure, negotiating delivery schedules and routing plans under constraints such as time windows and capacity [15,16].

Recent work proposes intelligent MAS for city logistics and last-mile delivery, where agents coordinate parcel deliveries, micro-hubs, and crowdsourced couriers in highly dynamic urban environments [16].

These systems incorporate real-time traffic conditions, customer preferences, and environmental constraints to optimize routing and consolidation decisions, often through combined simulation–optimization approaches [17,38].

In addition, multi-agent decision support has been developed for transportation regulation and traffic management, where agents model regulators, drivers, and infrastructure to propose control strategies [35,62]. Agent-based simulation has also been used to study the co-evolution of logistics clusters and the transfer of knowledge among the firms that compose them [63].

4.2 Warehousing, picking, and inventory management

In warehousing, agent-based decision support has been applied to order picking and to the coordination of robotic and human workers. Krnjaic et al. [19] develop a hierarchical multi-agent reinforcement learning approach in which a manager agent assigns picking tasks to robot and human worker agents, improving pick rates and sample efficiency relative to heuristic baselines across several warehouse layouts and both person-to-goods and goods-to-person picking paradigms.

Minashkina and Happonen [64] systematically review the literature that links Warehouse Management Systems (WMS) with social and environmental sustainability. Searching Scopus and Web of Science for the period 2006–2022, they identify only 12 relevant articles, published between 2013 and 2022 in business, engineering, computer science, and the social sciences. The review finds that social sustainability receives more attention than environmental sustainability, that the Internet of Things and Industry 4.0 technologies are recurring themes, and that integrating WMS with complementary systems supports warehouse sustainability objectives.

Agent-based and multi-agent models are also proposed for multi-echelon inventory control, where agents monitor stock levels across facilities and negotiate orders and replenishment policies to mitigate the bullwhip effect [2,20].

Fuzzy–rough sets and other AI techniques are integrated into multi-agent analytics frameworks to configure supply chains and inventory strategies in dynamic environments [12].

4.3 Production, maintenance, and material management

In production and material management, MAS supports production scheduling, maintenance planning, and material flow control. Multi-agent system architectures have been proposed to coordinate production orders, machine agents, and logistics agents under dynamic demand and disturbances [9,41].

Agent-based models have also been applied to improve supply chain design and configuration processes, as well as modular vehicle fleets, integrating production and logistics decisions [10,21].

Multi-agent analytics frameworks facilitate the configuration of distributed manufacturing networks based on multiple-criteria performance measures [12].

4.4 Resilience, risk management, and humanitarian logistics

A growing body of work uses MAS to enhance supply chain resilience and risk management. Chen et al. [23] review agent-based modeling for supply chain risk, concluding that Agent-based Modeling and Simulation (ABMS) and MAS are well-suited to capture cascading disruptions and adaptive behaviors. They examine how ABMS has been applied to Supply Chain Risk Management (SCRM), arguing that traditional methods struggle to capture the complexity, interactivity, and adaptability of modern supply networks. Through a multi-perspective survey, the authors classify existing ABMS research along three dimensions: risk-management processes (identification, assessment, response, and monitoring/evaluation), planning decision levels (strategic, tactical, and operational), and supply chain design goals (robustness and flexibility). The researchers highlight that while ABMS provides significant advantages—such as modeling distributed autonomous agents, heterogeneous interactions, and dynamic disruptions—it remains under-utilized in SCRM studies, and more work is needed.

Similarly, Bugert and Lasch [24] combined agent-based modeling with Bayesian networks to analyze risk propagation within supply networks. Their findings demonstrate how local disruptions can spread both upstream and downstream throughout the supply chain.

Likewise, Nadi and others [25] developed a multi-agent decision support system for time-slot allocation at container terminals. The proposed system explicitly models agents' reactions to disturbances and uncertainty, enabling more efficient logistics operations management.

In humanitarian logistics, Rodríguez-Espíndola and others [26] conduct a systematic review of 105 articles on optimization models, assessing how effectively decision-makers (practitioners) are involved in model design and deployment. The authors find that only about 10% of studies actively engage practitioners in modeling decisions, and fewer than 22% propose new solution methods that deliver results within practical decision-making time horizons. The objectives in existing models often diverge significantly from the priorities of field practitioners, and environmental concerns are inadequately incorporated, despite being a top global agenda item. The review demonstrates that limited practitioner engagement and long computation times hinder real-world implementation of optimization models in humanitarian logistics. Accordingly, the authors advocate for more inclusive modeling processes, faster solution methods, and broader incorporation of sustainability and environmental objectives to enhance relevance and adoption.

Liao and others [27] developed an agent-based simulation model to compare three post-disaster humanitarian logistics structures: Agency-Centric Efforts (ACEs), Partially Integrated Efforts (PIEs), and Collaborative Aid Networks (CANs). The study examines how agent behaviors, including affected individuals, relief organizations, and shelters, and coordination mechanisms, such as information sharing and crowd movement, influence the performance of relief distribution systems. The results indicate that higher distribution capacity and advanced coordination mechanisms, particularly in CANs, significantly reduce deprivation costs and waiting times for affected populations. Although information sharing improves system performance, its marginal benefits gradually diminish. Additionally, restricting crowd movement through temporary shelters reduces demand uncertainty and enhances supply chain responsiveness.

These studies demonstrate how agents representing relief organizations, facilities, vehicles, and affected populations can support decision-makers in exploring alternative response strategies and evaluating trade-offs among speed, coverage, and equity.

5 Cross-cutting benefits and challenges

5.1 Reported benefits

Recent studies demonstrate that Multi-Agent Systems deliver measurable operational benefits across diverse logistics environments. González-Cancelas and others [65] propose a structured MAS architecture for Roll-on/Roll-off terminal management in which six specialized agents handle space allocation, route planning, traffic control, and boarding coordination. Their comparative analysis against traditional port management models indicates that agent-based automation can reduce vehicle dwell time by up to 25%, minimize unnecessary travel through dynamic routing, and improve ramp utilization through synchronized scheduling. Beyond efficiency gains, the study highlights that MAS integration supports sustainability objectives by lowering energy consumption and aligning terminal operations with Industry 4.0 principles of real-time decision-making, interoperability, and decentralized coordination. Across the reviewed literature, the main benefits of AI agents for logistics decision-making are:

- Improved responsiveness and real-time adaptation. MAS can react to local events without requiring global re-optimization, enabling more agile responses to disruptions [16,62].
- Handling of complexity and distribution. Agent-based models decompose large logistics systems into interacting entities, thereby improving scalability and enabling heterogeneous decision rules [5,13].
- Enhanced resilience and robustness. Agents facilitate scenario analysis and self-healing behaviors, in which logistics networks reconfigure routes, capacities, and sourcing in response to disruptions [25-27].
- Support for collaboration and privacy. Several architectures maintain detailed data locally while sharing aggregated information or decisions through agent interactions, which is crucial for inter-organizational supply chains [65].

- Scalability and modularity. New agents (e.g., additional warehouses, carriers, terminals) can be added with limited changes to the system, supporting incremental deployment [14,39].

5.2 Challenges and limitations

Key challenges highlighted in the literature include:

- Integration with legacy systems. Many logistics operations rely on ERP, WMS, and TMS platforms; therefore, integrating MAS-based decision modules requires interoperability standards and robust APIs [9,22].
- Data quality and availability. Agentic AI depends on reliable and timely data. Data gaps or inconsistencies may compromise decision-making processes, particularly when learning-based agents are employed [28].
- Model validation and explainability. Validating agent behavior and explaining recommendations to human operators are essential, especially in safety-critical operations [5,23,24].
- Governance and accountability. As agents evolve from advisory roles to autonomous decision-making, organizations must establish clear governance frameworks, operational constraints, and accountability mechanisms for AI-driven decisions [66].
- Human-AI collaboration. Several studies emphasize the importance of designing interfaces, escalation mechanisms, and training processes that enable planners to understand, override, or refine agent recommendations. The literature also warns against both overreliance on and distrust of autonomous systems, highlighting the importance of training, interpretability, and shared control. Finally, the authors propose a research agenda focused on the responsible and human-centered adoption of AI in supply chains [67].

6 Results and discussion

Analysis of the 60 core papers reveals that the majority remain at early stages of empirical validation. Of the reviewed studies, 8 (13%) report deployment or pilot implementation in real operational settings, while the remaining 52 (87%) are conceptual, simulation-based, or limited to controlled experimental environments. This distribution reflects a persistent gap between theoretical agent-based models and industry-ready decision-support tools, and highlights the need for more applied research bridging this divide.

Regarding agent architecture, the reviewed literature shows a clear dominance of Multi-Agent Systems, which account for 55 of the 60 studies (92%), while single-agent approaches represent the remaining 5 (8%). This distribution reflects the inherently distributed and interdependent nature of logistics operations, where coordination among multiple autonomous entities, each managing a specific function such as routing, scheduling, or inventory control, offers greater flexibility and scalability than centralized single-agent designs.

The reviewed studies span all three levels of logistics decision-making, though with uneven coverage. Operational and tactical decisions are the most frequently addressed, each appearing in 22 studies (37%), followed by strategic decisions in 10 (17%) and execution-level applications in the remaining 6 (10%). The relative underrepresentation of strategic-level applications suggests that AI agent deployment remains closer to day-to-day operational optimization than to long-term network design or policy decisions, pointing to an area where future research could expand the scope of agent-based contributions.

A notable diversity of AI techniques is observed across the reviewed studies. Simulation and agent-based modeling (ABM) are the most frequently applied approaches, each appearing in 4 studies, followed by rule-based systems, negotiation agents, and hybrid approaches, each appearing in 3 studies. The remaining papers employ a wide range of methods, including heuristics, hybrid models, Bayesian learning, neural networks, and machine learning. Grouping these into broader categories, simulation-based techniques account for approximately 37% of the corpus, while learning-based approaches, including reinforcement learning and machine learning variants, represent around 18%, reflecting a gradual shift toward data-driven methods in more recent contributions.

A temporal analysis of the 60 core papers reveals a clear upward trend in research output. Publications before 2015 account for 23 studies, while those from 2015 to 2025 contribute the remaining 37, with a pronounced acceleration after 2019: the years 2020, 2021, and 2023 alone account for 20 papers (33% of the total corpus). This growth coincides with broader advances in machine learning, increased availability of real-time logistics data, and the disruptions to global supply chains triggered by the COVID-19 pandemic, all of which appear to have intensified academic interest in intelligent, adaptive decision-support systems.

7 Conclusions

This paper reviews the literature on AI agents for decision support in logistics operations. The reviewed studies indicate that intelligent agents and Multi-Agent Systems (MAS) provide a promising paradigm for addressing the complexity, dynamism, and distributed nature of modern logistics systems. Applications across transportation, warehousing, production, and resilience management demonstrate significant potential to enhance responsiveness,

AI agents for decision support in logistics management: a literature review

Diana Sánchez-Partida, Emmy Getsel Sánchez-Cordova, Manuel Romero-Julio

efficiency, and robustness. However, the literature also highlights persistent challenges related to system integration, data management, governance, and human–AI collaboration.

The reviewed literature suggests that most agent-based models rely on simplified structures, static assumptions, or hypothetical datasets, which limit empirical validation and reduce practical decision-support value. Several authors emphasize the need for more data-driven ABMS frameworks that integrate real-time sensor data, digital twin inputs, and stochastic demand signals to improve model fidelity, calibration, and industrial applicability.

Existing studies rarely capture how disruptions propagate across multi-tier networks or how autonomous agents collaborate, negotiate, and adapt within dynamic risk environments. According to the literature, distributed coordination mechanisms, including decentralized optimization, cooperative game theory, and reinforcement learning, may improve the simulation of emergent behaviors and adaptive resilience strategies across global supply chains.

The reviewed applications frequently operate in isolation, with limited integration of structured risk frameworks, scenario-based planning, and optimization-based mitigation models. Based on the identified gaps, future research should consider incorporating frameworks such as ISO 22301, Business Continuity Management Systems (BCMS), ISO 31000, Risk Management Guidelines, and ISO 28000, Security Management in the Supply Chain. Furthermore, several studies suggest developing hybrid approaches that integrate ABMS with robust optimization, agent-based decision support, and risk-aware planning systems to evaluate mitigation strategies, quantify resilience, and support real-time decision-making under uncertainty.

Significant gaps identified in MAS and humanitarian logistics research include limited practitioner involvement: approximately 10% of studies incorporate decision-makers into model design. The literature suggests that future research should promote the co-creation of models with humanitarian practitioners by incorporating their objectives, constraints, and operational preferences early in the modeling lifecycle, thereby increasing the relevance and adoption of these systems. On the one hand, several studies report that existing solution methods often lack practical timeliness, with fewer than 22% delivering results within decision-sensitive timeframes. Consequently, there is a need for faster, more scalable optimization algorithms that can deliver actionable solutions during crises rather than relying solely on offline methods. On the other hand, environmental and sustainability objectives remain insufficiently integrated into humanitarian logistics models despite their growing global relevance. The reviewed studies suggest that this limitation may be addressed by incorporating environmental sustainability indicators — such as carbon emissions, circular logistics, and resource scarcity — together with multi-criteria decision-making approaches that balance humanitarian, economic, temporal, and ecological objectives.

Overall, the literature suggests that intelligent agents and multi-agent systems constitute a powerful yet underexplored paradigm for humanitarian logistics, disaster risk reduction, and resilience building. Nevertheless, most existing applications remain conceptual or simulation-based and continue to focus primarily on traditional commercial supply chains. Future research should therefore focus on designing, implementing, and empirically validating agent-based systems capable of supporting end-to-end humanitarian logistics operations, including early warning systems, needs assessment, pre-positioning strategies, dynamic allocation of scarce resources, and last-mile delivery under conditions of extreme uncertainty. In addition, several authors emphasize the importance of integrating risk information, climate scenarios, and social vulnerability indicators into agent architectures to improve continuity planning before, during, and after disruptive events. The literature also highlights the importance of developing human-centered agents that collaborate with emergency managers, local communities, and non-governmental organizations (NGOs), rather than replacing them, in order to ensure the legitimacy, transparency, and ethical use of AI technologies. Ultimately, advances in agent-based decision support may contribute not only to faster and more efficient emergency responses but also to long-term resilience and the protection of lives and livelihoods in the face of recurrent crises.

Finally, the reviewed studies emphasize the importance of developing hybrid architectures that incorporate human-centered design principles and ESG-oriented performance metrics. Future developments in agentic AI are expected to reshape decision-making and coordination processes across logistics networks by enabling more adaptive, collaborative, and data-driven operations. In this context, future research may focus on integrating intelligent agents with real-time analytics, digital twins, sustainability frameworks, and risk-aware planning systems to improve resilience and operational responsiveness. Moreover, the literature suggests that human-centered AI systems capable of supporting, rather than replacing, human decision-makers could play a critical role in humanitarian logistics, disaster response, and complex supply chain management. Ultimately, advances in agent-based decision support may contribute to more efficient, transparent, and resilient logistics systems under increasingly uncertain and dynamic environments.

References

- [1] BARYANNIS, G., VALIDI, S., DANI, S., ANTONIOU, G.: *Decision Support Systems and Artificial Intelligence in Supply Chain Risk Management*, In: Zsidisin, G., Henke, M. (eds) *Revisiting Supply Chain Risk*. Springer Series in Supply Chain Management, Vol 7., Springer, Cham., pp. 53-71, 2018. https://doi.org/10.1007/978-3-030-03813-7_4
- [2] KAIHARA, T.: Multi-Agent Based Supply Chain Modelling With Dynamic Environment, *International Journal of Production Economics*, Vol. 85, No. 2, pp. 263-269, 2003. [https://doi.org/10.1016/S0925-5273\(03\)00114-2](https://doi.org/10.1016/S0925-5273(03)00114-2)

- [3] WADHWA, S., BIBHUSHAN: Supply Chain Modeling: The Agent Based Approach, *IFAC Proceedings Volumes*, Vol. 39, No. 3, pp. 471-476, 2006. <https://doi.org/10.3182/20060517-3-FR-2903.00247>
- [4] DOMINGUEZ, R., CANNELLA, S.: Insights on multi-agent systems applications for supply chain management, *Sustainability*, Vol. 12, No. 5, 1935, pp. 1-13, 2020. <https://doi.org/10.3390/su12051935>
- [5] XU, L., MAK, S., BRINTRUP, A.: Will Bots Take Over the Supply Chain? Revisiting Agent-Based Supply Chain Automation, *International Journal of Production Economics*, Vol. 241, 108279, 2021. <https://doi.org/10.1016/j.ijpe.2021.108279>
- [6] SINGH, R.: *Intelligent agents*, In: Bidgoli, H. (ed.), *Encyclopedia of Information Systems*, Elsevier, pp. 639-647, 2003. <https://doi.org/10.1016/B0-12-227240-4/00094-0>
- [7] HERZOG, O., TIMM, I.J.: *Intelligent Agents for Social and Learning Logistics Systems*, In: Freitag, M., Kotzab, H., Megow, N. (eds) *Dynamics in Logistics*. Springer, Cham., pp. 91-107, 2021. https://doi.org/10.1007/978-3-030-88662-2_5
- [8] GRUNDSPENKIS, J.: *Intelligent Agents in Logistics: Some Trends and Solutions*, 11th International Workshop on Harbor, Maritime & Multimodal Logistics Modeling & Simulation, HMS 2008, September 17-19, 2008, Campora S. Giovanni, Italy, Printed in Rende (CS), Italy, pp. 174-179, 2008.
- [9] GOVINDU, R., CHINNAM, R.B.: MASCF: A Generic Process-Centered Methodological Framework for Analysis and Design of Multi-Agent Supply Chain Systems, *Computers & Industrial Engineering*, Vol. 53, No. 4, pp. 584-609, 2007. <https://doi.org/10.1016/j.cie.2007.06.003>
- [10] AKANLE, O.M., ZHANG, D.Z.: Agent-Based Model for Optimising Supply-Chain Configurations, *International Journal of Production Economics*, Vol. 115, No. 2, pp. 444-460, 2008. <https://doi.org/10.1016/j.ijpe.2008.02.019>
- [11] JULKA, N., SRINIVASAN, R., KARIMI, I.: Agent-based supply chain management—1: framework, *Computers & Chemical Engineering*, Vol. 26, No. 12, pp. 1755-1769, 2002. [https://doi.org/10.1016/S0098-1354\(02\)00150-3](https://doi.org/10.1016/S0098-1354(02)00150-3)
- [12] SHUKLA, N., KIRIDENA, S.: A fuzzy rough sets-based multi-agent analytics framework for dynamic supply chain configuration, *International Journal of Production Research*, Vol. 54, No. 23, pp. 6984-6996, 2016. <https://doi.org/10.1080/00207543.2016.1151567>
- [13] BÖHNLEIN, D., SCHWEIGER, K., TUMA, A.: Multi-agent-based transport planning in the newspaper industry, *International Journal of Production Economics*, Vol. 131, No. 1, pp. 146-157, 2011. <https://doi.org/10.1016/j.ijpe.2010.04.006>
- [14] SCHLEIFFER, R.: Intelligent agents in traffic and transportation, *Transportation Research Part C: Emerging Technologies*, Vol. 10, No. 5-6, pp. 325-329, 2002. [https://doi.org/10.1016/S0968-090X\(02\)00029-3](https://doi.org/10.1016/S0968-090X(02)00029-3)
- [15] BAZZAN, A.L.C., KLÜGL, F., OSSOWSKI, S.: Agents in traffic and transportation: Exploring autonomy in logistics, management, simulation, and cooperative driving, *Transportation Research Part C: Emerging Technologies*, Vol. 13, No. 4, pp. 251-254, 2005. <https://doi.org/10.1016/j.trc.2005.07.001>
- [16] KAHALIMOGHADAM, M., THOMPSON, R.G., RAJABIFARD, A.: An intelligent multi-agent system for last-mile logistics, *Transportation Research Part E: Logistics and Transportation Review*, Vol. 200, 104191, pp. 1-40, 2025. <https://doi.org/10.1016/j.tre.2025.104191>
- [17] HELO, P., ROUZAFZON, J.: An Agent-Based Simulation and Logistics Optimization Model for Managing Uncertain Demand in Forest Supply Chains, *Supply Chain Analytics*, Vol. 4, pp. 1-12, 2023. <https://doi.org/10.1016/j.sca.2023.100042>
- [18] SALAS-RODRÍGUEZ, D., RIVAS-TOVAR, L.A.: Agent-based modelling for evaluation of transportation mode selection in the State of Guanajuato, Mexico, *Computación y Sistemas*, Vol. 26, No. 4, pp. 1689-1701, 2022. <https://doi.org/10.13053/cys-26-4-3989>
- [19] KRINJAIC, A., STELEAC, R.D., THOMAS, J.D., PAPOUDAKIS, G., SCHÄFER, L., TO, A.W.K., LAO, K.-H., CUBUKTEPE, M., HALEY, M., BÖRSTING, P., ALBRECHT, S.V.: Scalable Multi-Agent Reinforcement Learning for Warehouse Logistics with Robotic and Human Co-Workers, *arXiv preprint*, arXiv:2212.11498, 2024. <https://doi.org/10.48550/arXiv.2212.11498>
- [20] UM, W., LU, H., HALL, T.J.K.: A Study of Multi-Agent Based Supply Chain Modeling and Management, *iBusiness*, Vol. 2, No. 4, pp. 333-341, 2010. <https://doi.org/10.4236/ib.2010.24043>
- [21] LI, X., EPUREANU, B.I.: An agent-based approach to optimizing modular vehicle fleet operation, *International Journal of Production Economics*, Vol. 228, 107733, pp. 1-12, 2020. <https://doi.org/10.1016/j.ijpe.2020.107733>
- [22] TERRADA, L., EL KHAÏLI, M., OUAJJI, H.: Multi-agents system implementation for supply chain management making-decision, *Procedia Computer Science*, Vol. 177, pp. 624-630, 2020. <https://doi.org/10.1016/j.procs.2020.10.089>
- [23] CHEN, X., ONG, Y.-S., TAN, P.-S., ZHANG, N., LI, Z.: *Agent-Based Modeling and Simulation for Supply Chain Risk Management - A Survey of the State-of-the-Art*, 2013 IEEE International Conference on Systems, Man, and Cybernetics, 13-16 October, Manchester, UK, pp. 1294-1299, 2013. <https://doi.org/10.1109/SMC.2013.224>

- [24] BUGERT, N., LASCH, R.: Analyzing upstream and downstream risk propagation in supply networks by combining agent-based modeling and Bayesian networks, *Journal of Business Economics*, Vol. 93, pp. 859-889, 2023. <https://doi.org/10.1007/s11573-022-01128-2>
- [25] NADI, A., SNELDER, M., VAN LINT, J.W.C., TAVASSZY, L.: A data-driven and multi-agent decision support system for time slot management at container terminals: a case study for the Port of Rotterdam, *arXiv preprint*, arXiv:2311.15298, 2023. <https://doi.org/10.48550/arXiv.2311.15298>
- [26] RODRÍGUEZ-ESPÍNDOLA, O., AHMADI, H., GASTÉLUM-CHAVIRA, D., AHUMADA-VALENZUELA, O., CHOWDHURY, S., DEY, P.K., ALBORES, P.: Humanitarian logistics optimization models: an investigation of decision-maker involvement and directions to promote implementation, *Socio-Economic Planning Sciences*, Vol. 89, 101669, pp. 1-26, 2023. <https://doi.org/10.1016/j.seps.2023.101669>
- [27] LIAO, H., HOLGUÍN-VERAS, J., CALDERÓN, O.: Comparative analysis of the performance of humanitarian logistic structures using agent-based simulation, *Socio-Economic Planning Sciences*, Vol. 90, 101751, pp. 1-20, 2023. <https://doi.org/10.1016/j.seps.2023.101751>
- [28] REZKI, N., MANSOURI, M.: Integrating machine learning and deep learning for enhanced supplier risk prediction, *Acta Logistica*, Vol. 11, No. 3, pp. 387-396, 2024. <https://doi.org/10.22306/al.v11i3.523>
- [29] DAVIDSSON, P., HENESEY, L., RAMSTEDT, L., TÖRNQUIST, J., WERNSTEDT, F.: An analysis of agent-based approaches to transport logistics, *Transportation Research Part C: Emerging Technologies*, Vol. 13, No. 4, pp. 255-271, 2005. <https://doi.org/10.1016/j.trc.2005.07.002>
- [30] ESPEJO-DÍAZ, J.A.: *On the dynamic inventory-routing problem in humanitarian logistics: a simulation-optimization approach using agent-based modelling*, Master's Thesis, Faculty of Engineering, Universidad de La Sabana, Chía, Colombia, 2020.
- [31] HERNÁNDEZ, J.E., ALEMANY, M.M.E., LARIO-ESTEBAN, F.C., POLER, R.: SCAMM-CPA: A supply chain agent-based modelling methodology that supports a collaborative planning process, *Innovar: Revista de Ciencias Administrativas y Sociales*, Vol. 19, No. 34, pp. 99-120, 2009.
- [32] LI, J., CHAN, F.T.S.: An agent-based model of supply chains with dynamic structures, *Applied Mathematical Modelling*, Vol. 37, No. 7, pp. 5403-5413, 2013. <https://doi.org/10.1016/j.apm.2012.10.054>
- [33] XU, L., MAK, S., MINARICOVA, M., BRINTRUP, A.: On implementing autonomous supply chains: a multi-agent system approach, *Computers in Industry*, Vol. 161, 104120, pp. 1-18, 2024. <https://doi.org/10.1016/j.compind.2024.104120>
- [34] JAIMEZ-GONZÁLEZ, C.R., LUNA-RAMÍREZ, W.A.: Towards a Multi-Agent System Architecture for Supply Chain Management, *arXiv preprint*, arXiv:2110.08125, 2021. <https://doi.org/10.48550/arXiv.2110.08125>
- [35] LUJAK, M., DUSPARIC, I., KLÜGL, F., VIZZARI, G.: Agents in traffic and transportation (ATT 2020), *AI Communications*, Vol. 34, No. 1, pp. 1-3, 2021. <https://doi.org/10.3233/AIC-201640>
- [36] MES, M., VAN DER HEIJDEN, M., SCHUUR, P.: Interaction between intelligent agent strategies for real-time transportation planning, *Central European Journal of Operations Research*, Vol. 21, pp. 337-358, 2013. <https://doi.org/10.1007/s10100-011-0230-7>
- [37] GERRITS, B., VAN HEESWIJK, W., MES, M.: Towards self-organizing logistics in transportation: a literature review and typology, *International Transactions in Operational Research*, Vol. 31, No. 3, pp. 1309-1374, 2024. <https://doi.org/10.1111/itor.13408>
- [38] MORENO, R.P.R., LOPES, R.B., RAMOS, A.L., FERREIRA, J.V., CORREIA, D., DE MELO, I.E.S.: An agent-based simulation and optimization approach for sustainable urban logistics: a case study in Lisbon, *Applied System Innovation*, Vol. 8, No. 3, 66, pp. 1-25, 2025. <https://doi.org/10.3390/asi8030066>
- [39] NITSCHKE, B., BRANDS, J., TREIBLMAIER, H., GEBHARDT, J.: The impact of multiagent systems on autonomous production and supply chain networks: use cases, barriers and contributions to logistics network resilience, *Supply Chain Management: An International Journal*, Vol. 28, No. 5, pp. 894-908, 2023. <https://doi.org/10.1108/SCM-07-2022-0282>
- [40] PAL, K.: Agent-Based Simulation for Supply Chain Transport Corridors, *International Journal of Computer and Information Engineering*, Vol. 9, No. 7, pp. 1677-1681, 2015. <https://doi.org/10.5281/zenodo.1107369>
- [41] STARUCH, T.: *Multi-agent systems for production planning*, Master's Thesis, Faculty of Electrical Engineering, Department of Control Engineering, Czech Technical University in Prague, Prague, 2023.
- [42] SWAMINATHAN, J.M., SMITH, S.F., SADEH, N.M.: Modeling supply chain dynamics: a multiagent approach, *Decision Sciences*, Vol. 29, No. 3, pp. 607-632, 1998. <https://doi.org/10.1111/j.1540-5915.1998.tb01356.x>
- [43] ULMER, M.W.: Dynamic Pricing and Routing for Same-Day Delivery, *Transportation Science*, Vol. 54, No. 4, pp. 1016-1033, 2020. <https://doi.org/10.1287/trsc.2019.0958>
- [44] LABELLE, A., FRAYRET, J.-M.: First-mile reverse logistics: an agent-based modelling and simulation application for glass bottle recovery, *Journal of Cleaner Production*, Vol. 422, 138574, pp. 1-11, 2023. <https://doi.org/10.1016/j.jclepro.2023.138574>

- [45] PARMAKSIZOGLU, I.A., BOMBELLI, A., SHARPANSKYKH, A.: A multi-agent optimization approach for multimodal collaboration in marine terminals, *Logistics*, Vol. 9, No. 3, 110, pp. 1-30, 2025. <https://doi.org/10.3390/logistics9030110>
- [46] HENESEY, L., DAVIDSSON, P., PERSSON, J.A.: *Evaluation of Automated Guided Vehicle Systems for Container Terminals Using Multi Agent Based Simulation*, In: David, N., Sichman, J.S. (eds.), *Multi-Agent-Based Simulation IX*, Lecture Notes in Computer Science, Vol. 5269, Springer, Berlin, Heidelberg, pp. 85-96, 2009. https://doi.org/10.1007/978-3-642-01991-3_7
- [47] REDDY, R.H., KUMAR, S.K., FERNANDES, K.J., TIWARI, M.K.: A Multi-Agent System based simulation approach for planning procurement operations and scheduling with multiple cross-docks, *Computers & Industrial Engineering*, Vol. 107, pp. 289-300, 2017. <https://doi.org/10.1016/j.cie.2016.11.008>
- [48] MACAL, C.M., NORTH, M.J.: Tutorial on agent-based modelling and simulation, *Journal of Simulation*, Vol. 4, No. 3, pp. 151-162, 2010. <https://doi.org/10.1057/jos.2010.3>
- [49] HENESEY, L., DAVIDSSON, P., PERSSON, J.A.: Agent based simulation architecture for evaluating operational policies in transshipping containers, *Autonomous Agents and Multi-Agent Systems*, Vol. 18, No. 2, pp. 220-238, 2009. <https://doi.org/10.1007/s10458-008-9044-y>
- [50] BASTARIANTO, F.F., HANCOCK, T.O., CHOUDHURY, C.F., MANLEY, E.: Agent-based models in urban transportation: review, challenges, and opportunities, *European Transport Research Review*, Vol. 15, 19, pp. 1-20, 2023. <https://doi.org/10.1186/s12544-023-00590-5>
- [51] ESPEJO-DÍAZ, J.A., GUERRERO, W.J.: A multiagent approach to solving the dynamic postdisaster relief distribution problem, *Operations Management Research*, Vol. 14, pp. 177-193, 2021. <https://doi.org/10.1007/s12063-021-00192-1>
- [52] FAN, Y., DE KLEUVER, C., DE LEEUW, S., BEHDANI, B.: Trading off cost, emission, and quality in cold chain design: A simulation approach, *Computers & Industrial Engineering*, Vol. 158, 107442, pp. 1-16, 2021. <https://doi.org/10.1016/j.cie.2021.107442>
- [53] FENG, S., DUAN, P., KE, J., YANG, H.: Coordinating ride-sourcing and public transport services with a reinforcement learning approach, *Transportation Research Part C: Emerging Technologies*, Vol. 138, 103611, pp. 1-19, 2022. <https://doi.org/10.1016/j.trc.2022.103611>
- [54] FIKAR, C., HIRSCH, P., NOLZ, P.C.: Agent-based simulation optimization for dynamic disaster relief distribution, *Central European Journal of Operations Research*, Vol. 26, No. 2, pp. 423-442, 2018. <https://doi.org/10.1007/s10100-017-0518-3>
- [55] KADDOUSSI, A., ZOGLAMI, N., HAMMADI, S., ZGAYA, H.: An agent-based distributed scheduling for crisis management supply chain, *International Journal of Computational Intelligence Systems*, Vol. 6, No. 1, pp. 156-173, 2013. <https://doi.org/10.1080/18756891.2013.761774>
- [56] MES, M., DOUMA, A.: *Agent-Based Support for Container Terminals to Make Appointments with Barges*, In: Paías, A., Ruthmair, M., Voß, S. (eds.), *Computational Logistics: 7th International Conference, ICCL 2016, Lecture Notes in Computer Science*, Vol. 9855, Springer, Cham, pp. 80-95, 2016. https://doi.org/10.1007/978-3-319-44896-1_6
- [57] HERNÁNDEZ, J.E., MULA, J., POLER, R., LYONS, A.C.: Collaborative Planning in Multi-tier Supply Chains Supported by a Negotiation-Based Mechanism and Multi-agent System, *Group Decision and Negotiation*, Vol. 23, pp. 235-269, 2014. <https://doi.org/10.1007/s10726-013-9358-2>
- [58] CHAN, C.-K., CHOW, H.K.H., SO, S.K.P., CHAN, H.C.B.: Agent-based flight planning system for enhancing the competitiveness of the air cargo industry, *Expert Systems with Applications*, Vol. 39, No. 13, pp. 11325-11334, 2012. <https://doi.org/10.1016/j.eswa.2012.02.031>
- [59] LI, W., NI, S.: Train timetabling with the general learning environment and multi-agent deep reinforcement learning, *Transportation Research Part B: Methodological*, Vol. 157, pp. 230-251, 2022. <https://doi.org/10.1016/j.trb.2022.02.006>
- [60] ZHOU, M., JIN, J., ZHANG, W., QIN, Z., JIAO, Y., WANG, C., WU, G., YU, Y., YE, J.: Multi-Agent Reinforcement Learning for Order-dispatching via Order-Vehicle Distribution Matching, *Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM 2019)*, 3-7 November, Beijing, pp. 2645-2653, 2019. <https://doi.org/10.1145/3357384.3357799>
- [61] WOOLDRIDGE, M.: *An Introduction to MultiAgent Systems*, 2nd ed., John Wiley & Sons, Chichester, 2009.
- [62] BALBO, F., PINSON, S.: Using intelligent agents for transportation regulation support system design, *Transportation Research Part C: Emerging Technologies*, Vol. 18, No. 1, pp. 140-156, 2010. <https://doi.org/10.1016/j.trc.2009.04.019>
- [63] SALAS-PENÁ, A., GARCÍA-PALOMARES, J.C.: Simulating co-evolution and knowledge transfer in logistic clusters using a multi-agent-based approach, *ISPRS International Journal of Geo-Information*, Vol. 14, No. 4, 179, pp. 1-25, 2025. <https://doi.org/10.3390/ijgi14040179>

AI agents for decision support in logistics management: a literature reviewDiana Sánchez-Partida, Emmy Getsel Sánchez-Cordova, Manuel Romero-Julio

- [64] MINASHKINA, D., HAPPONEN, A.: Warehouse management systems for social and environmental sustainability: a systematic literature review and bibliometric analysis, *Logistics*, Vol. 7, No. 3, 40, pp. 1-33, 2023. <https://doi.org/10.3390/logistics7030040>
- [65] GONZÁLEZ-CANCELAS, N., VACA-CABRERO, J., CAMARERO-ORIVE, A.: Multi-agent system for smart roll-on/roll-off terminal management: orchestration and communication strategies for AI-driven optimization, *Applied Sciences*, Vol. 15, No. 11, 6079, pp. 1-18, 2025. <https://doi.org/10.3390/app15116079>
- [66] SCHNEIDER, J., ABRAHAM, R., MESKE, C., VOM BROCKE, J.: Artificial Intelligence Governance for Businesses, *Information Systems Management*, Vol. 40, No. 3, pp. 229-249, 2023. <https://doi.org/10.1080/10580530.2022.2085825>
- [67] HENDRIKSEN, C.: Artificial intelligence for supply chain management: disruptive innovation or innovative disruption?, *Journal of Supply Chain Management*, Vol. 59, No. 3, pp. 65-76, 2023. <https://doi.org/10.1111/jscm.12304>

Review process

Single-blind peer review process.